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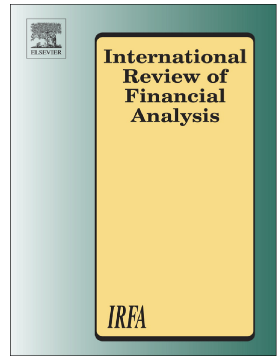

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The non-monotonic impact of bank size on their default swap spreads: cross-country evidence[1]

Nadia Benbouzid[#] Sushanta K. Mallick[±] Leone Leonida[2]

Abstract

This paper studies the drivers of bank's credit default swap (CDS) spread, taken as a measure of credit risk, by considering the impact of housing market along with a number of bank level determinants, such as regulatory capital, leverage, size, liquidity, asset quality and operations income ratio. We build upon a unique dataset consisting of 115 banks (during pre- and post-crisis periods) headquartered in 30 countries from both developed and emerging countries. Results suggest that CDS spread is driven by asset quality, liquidity and operations income ratio, while bank size is found to have a non-monotonic impact on CDS spread. If the bank is small, an increase in size reduces the average credit risk. If the bank is large enough, an increase in size raises the latter. From our results we derive the level of bank size that minimizes the CDS spreads. Financial institutions growing beyond this threshold are subject to higher credit risk, implying that smaller and medium sized banks are safer than large banks. When considering the estimates in the periods before and after the 2007 crisis, we further find a different extreme point of bank size in the former (approximately 1642 billion Euros) relative to a significantly lower level of optimal bank size (around 70 billion) in the post-crisis period, implying too-big-to-fail and too-big-to-save in the pre-crisis regime.

Keywords: Bank CDS spread, leverage, capital requirements, liquidity, asset quality, bank size, too-big-to-fail financial institutions, financial crisis.

JEL Classification: G01, G21, G32.

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This paper studies the drivers of bank's credit default swap (CDS) spread, taken as a measure of credit risk, by considering the impact of housing market along with a number of bank level determinants, such as regulatory capital, leverage, size, liquidity, asset quality and operations income ratio. We build upon a unique dataset consisting of 115 banks (during pre- and post-crisis periods) headquartered in 30 countries from both developed and emerging countries. Results suggest that CDS spread is driven by asset quality, liquidity and operations income ratio, while bank size is found to have a non-monotonic impact on CDS spread. If the bank is small, an increase in size reduces the average credit risk. If the bank is large enough, an increase in size raises the latter. From our results we derive the level of bank size that minimizes the CDS spreads. Financial institutions growing beyond this threshold are subject to higher credit risk, implying that smaller and medium sized banks are safer than large banks. When considering the estimates in the periods before and after the 2007 crisis, we further find a different extreme point of bank size in the former (approximately 1642 billion Euros) relative to a significantly lower level of optimal bank size (around 70 billion) in the post-crisis period, implying too-big-to-fail and too-big-to-save in the pre-crisis regime.

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1. Introduction

The recent financial crisis, which originated from the US housing market, is considered to be the worst crisis event since the 1929 Great Depression, when the crisis spread across sectors and countries via financial markets and balance sheet exposures (see Castrén and Rancan, 2014; Paltalidis et al., 2015). The reliance on financial engineering and securitization activities boosted mortgage issuance, and allowed dramatic credit expansion for more than a decade. However, since 2007, the credit boom era appeared to have been officially over when the housing market collapsed, financial markets froze, and banks and investors began defaulting. Default swaps as a well-known class of over-the-counter (OTC) derivatives then emerged as an important instrument of pricing default risk at different maturities – the so-called credit default swaps (CDS). Trading frictions, such as illiquidity and information asymmetries, can create price discrepancies from equilibrium (see, for example, Rubia et al., 2016). The excessive size and concentration of banking assumed away financial frictions that borrowers might default on their repayments (Goodhart, 2014). In order to make banks safer, following the financial crisis that was largely driven by an interaction between a housing boom and a bank credit expansion, restructuring banking systems, including dismantling universal banks into separate retail and investment parts, have been proposed by regulators. In this context, understanding the optimal size becomes important, below which too-big-to-fail doctrine is relevant where a bail-out guarantee will not be required, while too-big-to-save hypothesis may hold beyond the threshold level of bank size where a government is simply not able to bail them out.

Prior to the financial crisis there was the perception that big banks, should they face any solvency issues, would benefit from government protection and intervention. Most of the large financial institutions somewhat believed that by exceeding their optimal size, they would be categorized as *too-big-to-fail* and *too-important-to-fail* and would therefore never have to worry about their solvency. This possibly contributed to make the banks growing beyond their optimal size, exceeding the allowed leverage intakes and excessively increasing their lending activities to low-income (sub-prime) consumers. As the financial crisis unveiled, not all the systemically important banks benefited from a government bailout, nor government interventions necessarily stabilized the banking sector (see Kizys et al., 2016).

Actually, Lehman Brothers, which collapsed on the 15 September 2008, is among the brightest examples of a systemically important bank that was not saved by the Federal Reserve and the Treasury.

A limited literature has considered the recent financial crisis that led to the collapse of many systemically important banks which became bankrupt despite their size. These cases raise important questions of whether large banks are truly safer and face lower credit risk and narrower CDS spreads compared to smaller banks. Völz and Wedow (2011) suggest that CDS price is subject to distortion due to bank size, especially for those banks considered as *too-big-to-fail*. Some banks are larger than optimal and, as they tend to bear too high credit risk, they benefit from government support in case of negative events. Kane (2000) and Penas and Unal (2004) also suggest that large banks take over smaller financial institutions to expand in size. Penas and Unal (2004) examine bond returns and bond credit spreads close to the announcement of a merger over the period of 1991-1998, and show that medium-size banks have the ability to push the combined bank-asset size beyond the *too-big-to-fail* threshold after the merger. In turn, this leads to a higher reduction in the cost of funds compared to mega banks and small banks. This gives further incentives for banks to grow beyond the optimal size. However, Demirgüç-Kunt and Huizinga (2013) look at CDS and equity prices to investigate whether there are banks that are constrained by their size, and conclude that some banks are *too-big-to-save*.

Past literature also identifies the importance of the housing market, interest rates, yield spread and inflation as significant drivers of credit risk (Duffie & Singleton, 1999; Bevan & Garzarelli, 2000; Lekkos & Milas, 2001; In, Brown & Fang, 2003; Alexander & Kaeck, 2008; Naifar, 2010; Benbouzid and Mallick, 2013; and Benbouzid, Mallick, and Pilbeam, 2017). In addition, some authors look at bank-level factors driving CDS spread, and find that leverage, regulatory capital, liquidity and asset quality, as well as credit ratings tend to significantly impact credit risk (Fabozzi et al., 2007; Hull et al., 2004; Collin Dufresne et al., 2001; Campbell and Taksler, 2003; Benkert, 2004; and Chiaramonte and Casu, 2013). We include all these bank level determinants, also in line with Drago et al. (2017) who show that balance sheet determinants dominate market determinants for all banks

This paper addresses two key issues related to the CDS spread as a measure of credit risk. First, it considers the housing market and the bank level factors driving CDS spread including the financial crisis period. The second contribution of this paper is that it analyses whether larger banks are subject to higher credit risk compared to smaller banks. Our analysis brings important implications for future policies as developed countries are battling the previous lax regulatory regime. As such, identifying banks that are more prone to default helps the regulator to prevent the potential consequences that could arise during economic downturns. This can be achieved by establishing and designing specific set of rules and standards to be followed by riskier banks and financial institutions.

The findings of this paper suggest that the bank-level factors continue to be the significant drivers of the CDS spread. Although better housing market performance can give rise to higher risk-taking, the result remains less robust as this aggregate variable is correlated with the time fixed effect. Second, higher leverage is found to be positively associated with CDS spread. In addition, poor asset quality, and lower liquidity increase CDS spread. During the crisis period, the key drivers of the CDS spread was found to be asset quality, liquidity, operational income and bank size, where bigger, more liquid, better asset quality and operationally efficient banks were better able to cope with defaults. Leverage was found to be an important factor affecting the CDS spread during the pre-crisis period, with a positive impact on credit risk, thus implying that banks with higher levels of leverage were facing increased CDS spread due to their inability to repay their short-term liabilities. The effect however became insignificant in the dynamic model for the crisis period partly due to the deleveraging that took place following the crisis.

Finally, our main results on bank size suggest that bank size has a non-monotonic impact on the CDS spread. This implies that the bigger the bank, the higher the CDS spread, but only after the size exceeds a critical threshold. We allow for non-monotonicities in the model by including the squared term of bank size in the set of regressors, and find that the impact of the bank size on credit risk depends significantly upon the size of the bank. As such, our findings imply that when a small financial institution expands, the CDS spread level declines. If a large enough bank expands, it tends to face higher CDS spread and increased credit risk. This suggests the existence of an optimal bank size where, if a particular bank grows beyond this threshold level, it becomes more exposed to credit risk and subject to high CDS spreads. Using the preferred dynamic model, we derive the optimal size to be around 70 billion Euros for our sample, although the threshold level was much higher at 1642 billion Euros in the pre-crisis period indicating an increasing level of risk for excessively big banks.

The paper is organized as follows. Section 2 presents the literature and testable hypotheses. Section 3 presents the data. Section 4 present the empirical models. Section 5 discusses the empirical findings, and Section 6, finally concludes.

2. Prior literature and testable hypotheses

2.1. Too-big-to-fail and too-big-to-save? The impact of bank size upon credit risk

Before summer 2007, financial institutions and banks were expanding and growing in size, given the favorable economic climate. Credit expansion occurred on the back of low interest rates and exceptionally low funding costs. This allowed bigger banks to benefit and make very high profits. In addition, high foreign funding inflow was another factor that greatly contributed to banks' incentive to grow in size. Many small banks in Europe and across the Atlantic drastically expanded. Liabilities of the Iceland banking system surpassed the economy's GDP by 9 times in the last quarter of 2007. In a similar vein, the Swiss and the UK banking systems were also expanding beyond the recognized norm, surpassing the size of their GDP by 6.3 and 5.5 times, respectively. In France, Denmark, Belgium, Ireland and Netherlands, the banks' liabilities ratios were twice the size of their country's GDP. Finally, at least 30 banks globally were identified to have liabilities twice their countries' GDP, and 12 banks having a liability of over $1 trillion (Demirgüç-Kunt and Huizinga, 2013). These figures illustrate how banks and financial institutions have been expanding recklessly.

Bank size has been recently analyzed in the context of the CDS market (Völz and Wedow, 2013). The authors focused on investigating whether bank size reduces market discipline and found that, on average, market discipline exists in the CDS market. Nevertheless, the CDS prices are affected for banks that are considered as *too-big-to-fail*. A 1 percent rise in the bank size narrows the CDS spread for the same bank by approximately 2 points. Moreover, banks that are already systemically important may merge, thus becoming ever larger and narrowing the CDS spread on a much larger scale. This affects the entire banking system, because a narrower CDS spread signals a more stable bank, and instead it is likely that the CDS spread is narrower because of the large size only. In addition, the authors looked at the *too-big-to-save* phenomenon, and found that some banks attain a limit in their size where it becomes too hard for the government to intervene in case of a negative credit event or crisis, and offer bailout packages because of the high number of depositors expecting to be repaid and compensated.

Another stream of literature documents that bank size impacts the financial institutions' incentives to undertake risky investments and consequently affect its credit rating. Demsetz and Strahan (1997) show that large banks have higher lending capacity and can increase their debt exposure keeping at the same time a low level of credit risk. Furthermore, Sousa (2000) establishes that banks that are considered to be *too-big-to-fail* have a competitive advantage compared to smaller banks, as they find a difference of ratings of three credit notches. In the same vein, Rime (2005) also looks at bank size and credit ratings and find that bank size exhibits a positive and strong impact on issuer ratings. Sousa (2000) and Rime (2005) look at this relationship and find that large banks, that reached the threshold of being considered *too-big-to-fail*, enjoyed a considerably higher credit rating and could, therefore, benefit from a cheaper cost of funding compared to smaller banks. Similarly, Gómez-González and Kiefer (2009) also show that large banks have the tendency to experience less risk as they have the ability to diversify their assets in a more efficient way compared to smaller banks to lower their costs through economies of scale. Gómez-González and Kiefer (2009) look at bank size and bank failures, and find that small financial institutions are more prone to failure compared to larger financial institutions that have a risk diversification advantage.

In a similar vein, Mishkin (2006) focuses on the *too-big-to-fail* phenomenon and the reaction of large banks to the Federal Deposit Insurance Corporation Act (FDICIA) that was introduced in the early 90s. He finds that the issues associated with *too-big-to-fail* significantly diminishes after the introduction of FDICIA. This result is challenged by Boyd and Gertler (1993) and Ennis and Malek (2005). These authors argue that FDICIA gives large US banks higher incentives to invest in risky projects, as they had the safety net that the government would not let them down in case of financial difficulties because of the potential impact on the systemic stability. Banks that pursued the goal of joining the *too-big-to-fail* circle are found to go beyond their optimal size by taking over other smaller banks. This results in higher returns and narrower credit spreads; at the same time, causing an inefficient allocation of resources (Kane, 2000; Penas and Unal, 2004).

Also, Demirgüç-Kunt and Huizinga (2013) suggest that large banks are more prone to risk, focusing on whether the *too-big-to-save* or *too-big-to-fail* banks do exist in the real financial world. They use the CDS spread as an indicator of the approximate credit losses on banks' liabilities. Their findings suggest that there is a negative relationship between both the absolute and the systemic bank size with their book-to-market value. This, in turn, implies that if an already systemically important bank expands, it becomes *too-big-to-save* and exposes itself to higher credit risk.

The role of bank size has also been studied in the context of capital buffers. García-Suaza et al. (2012) focus on a panel of Columbian banks over the period of 1996-2010, and find that large banks behave differently with respect to small banks. The larger banks have a higher ability to obtain funding from capital markets and tend to keep their capital buffers low during credit expansions without necessarily exposing themselves to excessive risk. On the contrary, smaller banks are found to have barriers to access financial markets, and therefore face higher costs when trying to build their capital buffers. Hakenes and Schnabel (2011) also analyze bank size in relation to capital buffers and bank risk incentives. They look at the Basel 2 Capital Accord, and show that smaller banks are subject to higher risk taking activities if they are allowed to choose between the internal ratings-based, IRB, approach and the standardized approach to meet capital requirements. Smaller financial institutions tend to compete with larger banks that have such advantage and can lead to higher aggregate risk-taking activities.

Brown and Dinç (2011) study bank failure in the 1990s across 21 emerging countries. They design a specific risk hazard model, and show that if there are more banks with excessive level of leverage, the government is less likely to let the problematic bank to collapse in case financial assistance is required - this is also referred to as *too-many-to-fail* problem. Steever (2005), studies the role of bank size, credit as well as market risk in the context of the equity market. After focusing on the relationship between firm size and equity risk for commercial banks, the author finds that smaller banks have the tendency to issue loans which are deemed to be safer than those issued by larger banks. However, because the former banks are unable to diversify their risk exposures as efficiently as the latter, equity risk is almost the same for small and big banks. We therefore test the following hypothesis:

Hypothesis 1: CDS spread is non-monotonically associated with the bank's size.

In the light of the recent financial crisis, the functioning of financial markets has dramatically changed. As suggested by Demirgüç-Kunt and Huizinga (2013), large banks are more prone to risk, given that they engage in higher scale and riskier investments as compared to smaller banks. We therefore assume that before the financial crisis, larger banks faced reduced CDS spreads as they had the conviction to belong to the category of the *too-big-to-fail* banks. However, during the recent financial crisis, this phenomenon proved to be only limited to the very few big financial institutions that were more likely to affect the public.

2.2. Leverage effect

Past literature acknowledges the importance of a number of financial variables driving credit risk; these include: leverage, regulatory capital, asset quality and liquidity. Leverage was at the epicenter of debates among regulators, as one of the main factors contributing to the recent crisis. A number of authors incorporated leverage among other bank level and country level factors driving credit risk in terms of CDS spread and bond spread (Beltratti and Stulz, 2011; Annaert et al., 2013; Chiaramonte and Casu, 2013; and Benbouzid, Mallick and Sousa, 2017). Before 2007, banks and other financial institutions heavily relied on borrowing from capital markets beyond their real borrowing capacity, with debt to equity ratios exceeding 20 times their allowance for many large EU banks. Therefore, in case of a bank run, there was a high likelihood of bankruptcy, with the situation potentially deteriorating and causing contagion, followed by a systemic collapse of the entire financial system (Antao and Lacerda, 2011). In Bernanke and Gertler (1995), pro-cyclical leverage was found to have contributed to amplifying risk in the financial markets.

In addition, Fostel and Geanakoplos (2008) focused on emerging markets and showed that leverage cycles have the tendency to translate into contagion, causing a flight to collateral and creating volatility in financial markets. In a similar vein, Adrian and Shin (2008, 2009, 2010) demonstrate from their findings that leverage is countercyclical for non-financial US institutions, and pro-cyclical for investment banks. Pro-cyclical leverage has the ability to negatively impact on the business cycle, thus causing systemic instability. Kalemli-Ozcan et al. (2011) show evidence that investment banks tremendously expanded their leverage intakes through capital markets, and utilized their strong market power to attract additional funds. The presence of deposit insurance played another significant role during the process.

In Ericsson et al. (2009), CDS spreads were used in both levels and first-differences, demonstrating that their model was able to explain 23% of CDS spread fluctuations. The main variables that were found to drive the CDS spread were leverage and volatility, among other variables such as credit ratings, and market capitalization. Furthermore, authors including Christie (1982), Collin-Dufresne et al. (2001) and Alexander and Kaeck (2008) used bank stocks as a proxy for leverage, and found that higher levels of debt were positively associated with credit risk. However, Eom et al. (2004) contradict previous findings as their results showed that leverage had only limited power to affect bond spread as a proxy for credit risk.

Hypothesis 2: Higher leveraged banks impact positively on credit risk and CDS spreads.

We assume that leverage and credit default risk are positively associated. As such, when a bank starts heavily borrowing, the level of market capitalization becomes lower, while its leverage capacity starts exceeding its ability to repay investors. In addition, the financial institution becomes vulnerable to shocks and may easily go bust if there is a crisis. Over the period of 2007-2008, many banks were downgraded due to their excessive leverage intakes, which further hampered their ability to attract additional external funding, finally resulting in their collapse.

2.3. Effect of regulatory capital

A number of authors investigated the impact of regulatory capital and capital buffers on credit risk (Antao and Lacerda, 2011 and Chiaramonte and Casu, 2013). Previous literature states that traditionally banks held capital as a buffer against the risk of insolvency, and high level of liquid assets in order to protect themselves against unexpected high volume of bank withdrawals by depositors (Saidenberg and Strahan, 1999). However, through the increased use of securitization in the years leading to the financial crisis, and the high reliance on the new tools of risk management, many financial institutions escaped such regulatory requirements by shifting their debt to off balance sheet items. This allowed them to hold less capital to increase their lending activities, while complying with the necessary regulatory requirements (Gorton and Haubrich, 1990).

In Akhavein et al. (1997), systemically important banks were able to decrease their capital exposure and increase their lending operations after undergoing a merger. In addition, Demsetz and Strahan (1997) found that large banks have the capacity to engage in riskier lending activities, keeping at the same time a low level of capital. In a similar vein, Froot et al. (1993) and Froot and Stein (1998) analyzed lending practices for both financial and non-financial institutions and found that vigorous risk management enabled banks to conduct risky and illiquid investments and escape regulatory requirements, holding insufficient capital buffers during an unexpected crisis.

Previous literature also looks at various advanced models that banks used in order to optimize their capital structure by responding to different types of pressures from shareholders, debt holders and price fluctuations in the market (Flannery, 1994; Flannery and Sorescu, 1996; and Myers and Rajan, 1998). However, the recent financial crisis proved that the previous Basel 1 and Basel 2 Capital Accords were strongly criticized as it did not ensure the soundness of the regulatory financial system (Antao and Lacerda, 2011). Thus, in 2013, Basel 3 was introduced to strengthen the weak financial institutions' capital requirements, decreasing leverage intakes and raising liquidity levels.

Hypothesis 3: Higher capital buffers reduce credit risk and narrow the CDS spread.

The hypothesis is that regulatory capital is negatively related to the CDS spread. In fact, when banks have stronger capital buffers, in times of crisis, they are better equipped to sustain a shock, repay their outstanding liabilities and keep the bank in a stable condition, whereas a financial institution that has a low level of capital is very likely to go bankrupt if the financial system is hit by a crisis, especially with risk-averse investors losing confidence in the system and capital markets becoming reluctant to lend.

2.4. Liquidity effect

The drastic squeeze in the liquidity levels that followed the 2007-2008 financial crisis led to a dramatic decrease in the bank lending activities in the developed economies. Consequently, a stream of literature started developing in the last decade linking liquidity to credit risk, in the context of the recent banking crisis. Calice et al. (2009) looked at liquidity spill-overs in sovereign bond and CDS markets and found that for EU countries including Greece, Ireland and Portugal, liquidity of the sovereign CDS market has a strong time dependent impact on sovereign bond spreads. In a similar vein, De Socio (2013) looked at liquidity and credit risk in the Euro-interbank market, decomposing credit and liquidity components of the Euribor spread, by using CDS of various financial institutions. Their findings indicate that before August 2007 credit risk went up. In October 2008, the situation reversed with liquidity risk becoming the main driver of the Euribor spread. Mistrulli (2011) showed that bank-level liquidity shocks can be a channel for contagion as a bank default may spread to other banks through interbank linkages, while Paltalidis et al. (2015) provide evidence for other channels of transmission namely interbank, asset price, and sovereign credit risk markets in the banking network.

Furthermore, Diamond and Rajan (2005) looked at liquidity shortages in the context of banking crises, showing that bank failures typically lower liquidity levels reducing the already short liquidity reserves. This subsequently caused the level of credit default risk to go up and resulted in a contagion and collapse of the entire financial system. Similarly, Qiu and Yu (2012) looked at the determinants of liquidity provisions in the OTC market for credit default swaps, focusing on fluctuations of CDS liquidity across 732 firms during 2001-2008, and they find that big corporations near the investment-grade tend to have the highest liquidity levels. In addition, Berger and Bouwman (2010) related liquidity to monetary policy and show that during normal economic climate, there is a decrease in liquidity created by small banks, and liquidity creation is high before financial crises.

Hypothesis 4: Higher liquidity reduces credit risk and CDS spread.

We assume that liquidity and CDS spread are negatively related. The higher the liquidity level, the better the bank's ability to deal with large withdrawals and possible bank runs. During the recent financial crisis, banks faced huge liquidity shortage, with frozen capital markets which meant that there was no other source of liquidity to comply with investors' demand. Banks with stronger liquidity levels were able to sustain themselves, keeping their credit risk and CDS spread levels at moderate levels.

2.5. Asset quality effect

Credit rating agencies played an important role in the over-pricing of junk securities during the recent crisis; thus misleading investors and generating increased risk in the financial system (Caprio, 2010). In securitization, investors heavily rely on the credit ratings and bank ratios in order to access the asset quality of a particular security. As such, pools of mortgage loans were trenched into slices of senior, mezzanine and junior tranches, which were later sold according to their credit rating (Saunders and Allen, 1999). Thus, asset quality was very hard to be accurately captured, given that these structured securities were opaque and very different from traditional assets (Duffie, 2008). Even traders who specialized in instruments like Collateralized Debt Obligations (CDO) were hardly able to reflect, with certainty, on the quality of the underlying asset and its associated risk of default (Guo and Wu, 2014). Previous studies that used credit ratings to reflect on the asset quality as a driver of the CDS spread include Fabozzi et al. (2007) and Hull et al. (2004).

Besides credit ratings, past literature also identifies the importance of CAMEL indicators, which reflect on Capital, Asset quality, Management, Earnings and Liquidity characteristics for each particular bank. Curry et al. (2001) incorporated changes in CAMEL ratings in their research in order to uncover the ability of market data to predict bank financial distress. Similarly, Evanoff and Wall (2001) also used CAMEL indicators when investigating bank risk. Furthermore, Gropp et al. (2004) incorporated imaginary CAMEL ratings for each financial institution in their sample and found that asset quality among other indicators efficiently identified possible rating downgrades in the banking sector. Moreover, both Oshinsky and Olin (2006) and DeYoung et al. (2001) used CAMEL indicators to reflect on bank distress in the US and found that all of the financial variables, including asset quality, had significant explanatory power in affecting the probabilities of bank failure.

Asset quality was also used in previous research as a measure of credit risk. Otker-Robe and Podpiera (2010) looked at the determinants of credit default risk using three different bank level ratios to reflect asset quality, namely loan loss provisions to total loans, share of non-performing loans to total loans, as well as loan loss reserves ratios. Findings unveil that since the data did not look at the entire crisis period, asset quality was not found to be a significant driver of credit risk. Similarly, Chiaramonte and Casu (2013) also used the ratio of loan loss reserve to gross loans and the ratio of unreserved impaired loans to equity in order to reflect on the quality of bank assets when investigating the drivers of CDS spread. Furthermore, Koetter et al. (2010) investigated bank risk by using the ratio of non-performing loans to total assets as a measure of asset quality.

Hypothesis 5: higher asset quality reduces both CDS spread and credit risk.

We assume that the higher the asset quality, the narrower the CDS spread and credit risk. Thus when a bank is more cautious about the quality of the assets, it holds in its balance sheet and ensures that these assets are not of a toxic nature; in case there is a negative credit event, it becomes less prone to major default and bankruptcy.

3. Data and empirical model

3.1. Data

We look at 30 countries and 115 banks with annual data over the period 2004-2011. All the bank-level explanatory variables used to reflect bank characteristics are from Bankscope (Bureau Van Dijk). Table A.1 and Table A.2 describe the list of banks and countries under investigation. Data sources are summarized in Table 1, along with the tested hypotheses. The expected signs are arrived at by reviewing the literature and through visual inspections as displayed in Panel A to E of the Illustrative Graphs. Bank size which does not have an unambiguous sign requires further investigation in establishing a non-monotonic relationship as discussed in hypothesis 1.

The CDS for each bank is used in terms of the natural logarithm of the mid-spread. It has a 5-year maturity as it is the most liquid type of index and is denominated in the country's local currency and expressed in basis points. It is published by CMA and retrieved from Thomson Reuters Datastream.

The set of bank-level explanatory variables includes financial ratios which are drawn from the relevant literature as potential explanatory variables for the credit spreads as, among others, in Collin Dufresne et al. (2001), Campbell and Taksler (2003), Benkert (2004), Hull et al. (2004), Ötker-Robe and Podpiera (2010), Chiaramonte and Casu (2013), and Fabozzi et al. (2007). More specifically:

- House price data for each country is published by Oxford Economics, and retrieved from Thomson Reuters Datastream.

- Leverage is the ratio of long-term debt to common equity.
- Regulatory Capital is the Tier 2 Capital, computed as the difference between Total Capital and Tier 1 Capital.
- Asset Quality is the ratio of impaired loans to equity.
- Bank Liquidity is ratio of liquid assets to total deposits and borrowing.
- Operations Income Ratio is EBITA to average assets.
- Bank Size is the natural logarithm of the bank total assets.

Table 1
Description of variables

Variable		Description	Source	Expected sign
Dependent				
	ln(CDS)	Natural logarithm of the CDS in basis points, denominated in the country's local currency, 5 year, bank level, mid-spread.	CMA, from Thomson Reuters Datasteream	
Independent				
	ln(HP)	Natural logarithm of the House Price Index in basis points.	Oxford Economics, from Thomson Reuters Datastream	(-)
	Regulatory Capital	Tier 2 Capital = (Total Capital – Tier 1 Capital)	Bankscope	(-)
	Leverage	Long term debt to common equity	World Scope Fundamentals, from Thomson Reuters Datasteream	(+)
	Liquidity	Liquid Assets to Deposits and ST Funding	Bankscope	(-)
	Asset Quality	Impaired Loans to Equity	Bankscope	(+)
	Operations Income Ratio	EBITA to Average Assets	Bankscope	(-)
	Size	Log of Total Assets	Bankscope	(+/-)

3.2. The empirical model

We begin with estimating the following model:

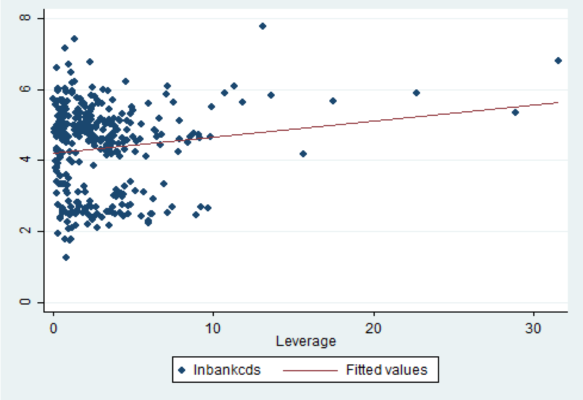
$$(1) \quad ln\ Bank\ CDS_{ij,t} = \beta_1 lnHP_{j,t} + \mu_i + \tau_t + \varepsilon_{ij,t},$$

where i is the bank, j is the economy, t is the year, $ln\ Bank\ CDS$ is natural logarithm of the bank CDS spread; *lnHP* is the natural logarithm of the house price index; μ_i is the Bank fixed effect; τ_t is the Time fixed effect and $\varepsilon_{ij,t}$ *iid* disturbance term.

The analysis of the empirical performance of Eq. (1) helps studying the impact of the presence of the time component of the error term on the estimate for β_1. The time component of the error term is important in controlling the estimated parameters for bank and time invariant determinants of CDS other than the house price, which are potentially omitted in the estimating equation.

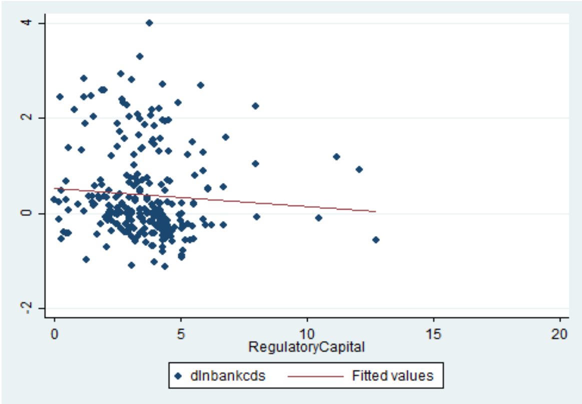
Illustrative graphs

Panel A: CDS spread (y axis) and Leverage



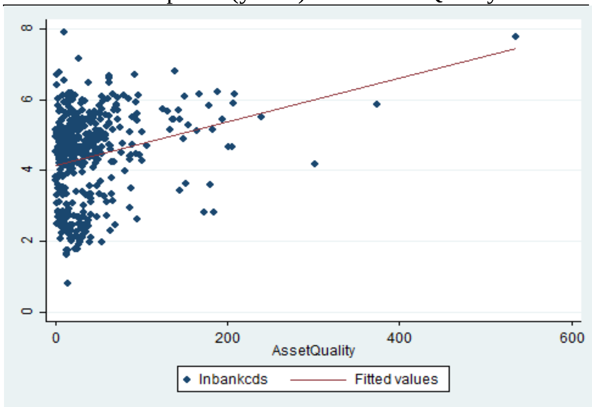
Note: Higher level of leverage tends to be associated with higher credit risk.

Panel B: CDS spread (y axis) and Regulatory Capital



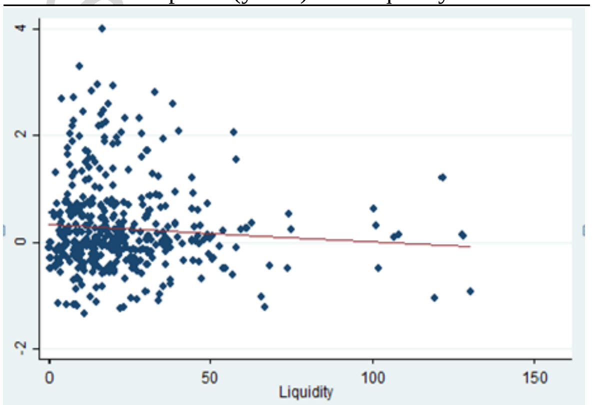
Higher regulatory capital tends to lower credit risk as reflected in CDS spreads.

Panel C: CDS spread (y axis) and Asset Quality



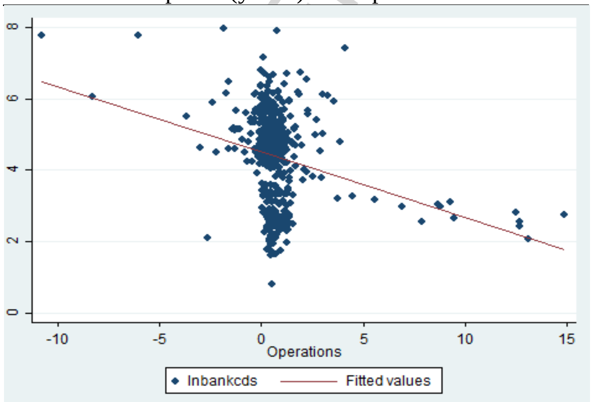
Lower asset quality (as reflected in higher bad loans on the *x* -axis) tends to increase credit risk.

Panel D: CDS spread (y axis) and Liquidity



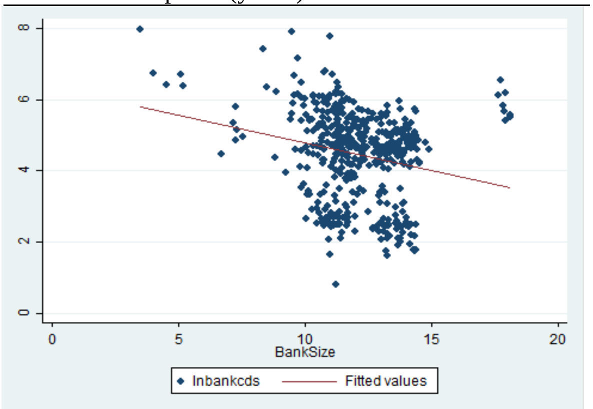
Higher liquidity on average tends to be associated with lower credit risk.

Panel E: CDS spread (y axis) and Operations Income



Higher operating income on average tends to be associated with lower credit risk.

Panel F: CDS spread (y axis) and Bank Size



Larger banks tend to have lower credit risk, although the relationship appears to be non-monotonic.

However, the house price index is country-specific and hence it is bank-invariant. This complicates the use of time effects, as these are bank-invariant as well. Strictly speaking time dummies can be included in that the variability can occur at country-level. On the other hand, there exists a problem of near collinearity between the house price index and time effects. Yet without time dummies, the question would arise whether the house price index would capture effects other than that we are interested in.

To determine how far this is and gauge the impact of this modelling decision on our empirical results, we compare the results and statistical performance from Eq. (1) with that produced by two other models:

$$(2) \quad ln\ Bank\ CDS_{ij,t} = \mu_i + \tau_t + \varepsilon_{ij,t},$$

and

$$(3) \quad ln\ Bank\ CDS_{ij,t} = \beta_1 lnHP_{j,t} + \mu_i + \varepsilon_{ij,t}.$$

The comparison between Eq. (1) and (2) provides information about the role of $lnHP_{j,t}$ as against that of the time effects on their own that, in turn, control for all the bank-invariant macroeconomic variables that potentially affect the bank's CDS. The comparison between Eq. (1) and (3) provides information on the effect of near multi-collinearity on our estimated parameters, and on how much explanatory power we may lose by not including time effects in the set of regressors.

Having decided the structure of the error term and studied the role of near perfect multicollinearity on the estimate, we generalize the estimating model by including a number of potential determinants of the bank's CDS in the set of regressors:

$$\begin{aligned}(4) \quad ln\ Bank\ CDS_{ij,t} &= \beta_1 lnHP_{ij,t} + \beta_2 Asset\ Quality_{ij,t} + \beta_3 Liquidity_{ij,t} \\ &+ \beta_4 Regulatory\ Capital_{ij,t} + \beta_5 Leverage_{ij,t} + \beta_6 Operations_{ij,t} \\ &+ \mu_i + \tau_t + \varepsilon_{ij,t},\end{aligned}$$

where *Asset Quality* is the impaired loans/equity ratio; *Liquidity* is liquid assets to total deposits and short-term funding; *Regulatory Capital* is the tier 2 capital; *Leverage* is the long-term debt to common equity and *Operations* is the EBITA over average assets.

We then generalize the model to consider the impact of bank size, explicitly allowing for potential non-monotonicities of the impacts of interest, by adding the natural logarithm of bank total assets, $ln\ Bank\ size$, and its squared value, to the set of regressors:

$$(5) \quad ln\ Bank\ CDS_{ij,t} = \beta_1 lnHP_{ij,t} + \beta_2 Asset\ Quality_{ij,t} + \beta_3 Liquidity_{ij,t} + \beta_4 Regulatory\ Capital_{ij,t} + \beta_5 Leverage_{ij,t} + \beta_6 Operations_{ij,t} + \beta_7 Ln\ Bank\ Size_{ij,t} + \beta_8 Ln\ Bank\ Size^2_{ij,t} + \mu_i + \tau_t + \varepsilon_{ij,t},$$

All models are estimated both *via* the Fixed effects and the Random Effects estimators. The fixed effects model controls for the effects of time-invariant variables with time-invariant effects. Therefore, it permits controlling for any unobserved country-specific time-invariant effects in the data, by conditioning them out and taking deviations from time averaged individual means. The result of this is the removal of any long-run variation in the dependent variable. In a random effects model, the unobserved variables are assumed to be statistically independent of all the observed variables. We report the preferred model based upon the Hausman test.

In estimating Eq (5), we implicitly assume that the impact of the independent variables on the bank CDS is constant over time. This is a strong assumption which impacts upon the estimates and is worth studying rather than imposing at the outset, given that the period under investigation contains the 2007 financial crisis. We proceed with two exercises. In a first exercise, we estimate Eq. (5) using the subsample of observations from 2004 to 2007, and from 2008 to 2011. This allows us to study whether the financial crisis had a significant role in changing the impact of the independent variables on the bank's CDS.

As a second exercise, we allow explicitly for dynamics in the estimating model. We assume that the observed CDS of the bank i, $ln\ Bank\ CDS_{ij,t}$, adjusts gradually to its equilibrium level, $ln\ Bank\ CDS^{E}_{ij,t}$ because of the role of time in taking measurement and potential institutional inertia:

$$(6)\quad ln\ Bank\ CDS_{ij,t} - ln\ Bank\ CDS_{ij,t-1} = \lambda(ln\ Bank\ CDS^{E}_{ij,t} - ln\ Bank\ CDS_{ij,t-1}),$$

where the actual change in observed bank's CDS is a fraction λ of the adjustment to its equilibrium, and $0<\lambda\leq 1$, captures the delay in the adjustment process. In turn, the equilibrium level is defined as:

$$\begin{aligned}(7)\quad ln\ Bank\ CDS^{E}_{ij,t} &= \beta_1 lnHP_{ij,t} + \beta_2 Asset\ Quality_{ij,t} + \beta_3 Liquidity_{ij,t} \\ &+ \beta_4 Regulatory\ Capital_{ij,t} + \beta_5 Leverage_{ij,t} + \beta_6 Operations_{ij,t} \\ &+ \beta_7 Ln\ Bank\ Size_{ij,t} + \beta_8 Ln\ Bank\ Size^{2}_{ij,t} + \mu_i + \tau_t + \varepsilon_{ij,t}.\end{aligned}$$

Combining Eq. (6) with Eq. (7) gives the following estimating model:

$$\begin{aligned}(8)\quad ln\ Bank\ CDS_{ij,t} &= \rho ln\ Bank\ CDS_{ij,t-1} + \theta_1 lnHP_{ij,t} + \theta_2 Asset\ Quality_{ij,t} \\ &+ \theta_3 Liquidity_{ij,t} + \theta_4 Regulatory\ Capital_{ij,t} \\ &+ \theta_5 Leverage_{ij,t} + \theta_6 Operations_{ij,t} \\ &+ \theta_7 Ln\ Bank\ Size_{ij,t} + \theta_8 Ln\ Bank\ Size^{2}_{ij,t} + \omega_i + \pi_t + \epsilon_{ij,t},\end{aligned}$$

where $\rho = 1 - \lambda, \theta = \lambda\beta$ for all the independent variables. As for the case of Eq. (5) we estimate Eq. (8) using both the entire sample period, and the subsample of observations from 2004 to 2007, and from 2008 to 2011. The two exercises allow us to study the extent to which estimated parameters are robust to significant variation over time of the economic environment. We note that, in Estimating Eq. (8), the joint presence of the lagged dependent variable and of the unobservable country-specific effects in the estimating model, makes the Within Group estimator unfeasible. This is because the lagged dependent variables and the bank fixed effects are necessarily correlated even if the idiosyncratic component of the error term is serially uncorrelated and the Within Groups estimator does not help as it is known to give downward biased estimates for ρ (Nickell, 1981). This discussion calls for the use of the DIF-GMM estimator in first instance (Arellano and Bond, 1991). This procedure removes the time invariant component of Eq. (8) by taking first difference, and exploits the dynamic properties of the data to generate instrumental variables, where particular care must be given to the choice of the set of instruments. We opt for the parsimonious approach as far as the sets of instruments are concerned, and use the *t-2* lag only for all the variables in the set of instruments.

4. Empirical results

4.1. Results on CDS determinants

We report results for the above models specified in the previous section. Results are summarised in Tables 2-4. According to the Hausman test, the FE model is the preferred method of estimation in the majority of the cases. Based on this evidence, we report parameters estimated with FE only. Standard errors are robust to autocorrelation and heteroscedasticity.

Results from the first Column of Table 2 suggest that the house price is not statistically significant, leading to the conclusion that the housing market has a neutral effect on credit risk in the benchmark model. Higher house prices are associated with higher CDS spreads, but the effect turns out to be insignificant when the time fixed effects are included in the set of regressors. As expected, indeed, the F-statistic shows that all regressors, i.e. the house price and the time dummies, are jointly statistically significant. This may be due to the near perfect collinearity between the variable and the time dummies. This is confirmed by results in Column (2) and (3), where the former shows that the house price is statistically significant if the time dummies are removed from the set of regressors, and the latter suggests that the statistics associated with the set of time times alone improve if the house price is removed from the set of regressors. This follows the economic rationale given that before summer 2007, real estate sector was continuously appreciating in value, banks were therefore subject to lower credit risk as not only they were able to regain the initial mortgage value if the borrower defaulted, but they could also earn a profit.

Our findings show that, in line with expectation, liquidity has a negative and statistically significant impact on CDS spread. This implies that liquid banks can cope better with large withdrawals and avoid bank-runs. The main responsibility of financial institutions is to provide liquidity to depositors and creditors by standing ready to offer them cash on demand. In the traditional framework, liquidity risk comes from the risk arising from bank-runs. This is a situation where depositors lose trust in their bank and withdraw their funds, driving investor sentiment down, either as a result of concerns about the bank's financial condition or because they worry that other depositors may also start withdrawing their funds, thus causing bank-runs. Such runs could make banks insolvent by initiating a chain reaction that may force a fire sale of illiquid loans. This in turn can result in bankruptcy of the financial institution.

Table 2
Parameters estimation

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	CDS spread (ln)							
House Price Index (ln)	0.919 (1.000)	3.243*** (0.715)		0.365 (1.070)	1.074 (1.081)	2.613** (1.124)	1.982 (1.536)	2.614* (1.550)
Liquidity (Liquid Assets / Dep & ST Funding)				-0.002 (0.002)	-0.004* (0.002)	-0.011** (0.005)	-######## (0.006)	-0.016** (0.007)
Asset Quality (Impaired Loans / Equity)					0.007*** (0.002)	0.011*** (0.002)	0.018** (0.007)	0.025*** (0.006)
Regulatory Capital (Tier 2 Capital)						-0.052 (0.040)	-0.142 (0.110)	-0.063 (0.112)
Leverage (Long-term debt to equity)							0.070** (0.031)	0.015 (0.026)
Operations Income Ratio (EBITA / Avg Assets)								######## (0.080)

Time dummies (joint)	97.24	-	111.93	96.93	40.03	24.96	9.89	10.76
Adjusted R^2	0.630	0.364	0.658	0.617	0.631	0.652	0.725	0.756
Hausman Specification test	29.94	32.34	23.54	20.42	31.46	13.78	16.26	44.26
All regressors (joint)	83.58	20.55	111.93	73.05	52.46	44.67	21.79	27.02
House Price Index (ln)	0.84	20.55	-	0.12	0.99	5.41	1.67	2.81

Notes: The sample includes 115 banks in 20 countries from 2004 to 2011. All the models include time dummies. Heteroskedasticity and autocorrelation consistent standard errors are clustered by country and reported in brackets. *** (**), [*] stands for the variable being statistical significant at 1% (5%) [10%] s.l.

Our results suggest that there is a somewhat unstable positive relationship between leverage and credit risk (CDS spread). Therefore, in case of a bank-run, there was a high likelihood of bankruptcy, which could potentially translate into a contagion and cause a systemic collapse of the entire financial system (Antão and Lacerda, 2011). When capital markets and money markets face shortage of liquidity, the only banks that are able to survive without the heavy reliance on borrowing from the lemon markets are those that hold higher levels of liquidity. In 2007, banks such as Northern Rock were unable to survive and had to be bailed out by the Bank of England as a result of bank-runs. In fact, as of September 2007, Northern Rock's liquidity gap within 3 months was more than £25 billion. As such, in less than one year, Northern Rock was under the obligation to refund £30 billion, with all the associated market risks (Congdon et al., 2009).

Our results are in line with Annaert et al. (2013) who find that the most important driver of credit risk in the Euro area was liquidity spread. Chiaramonte and Casu (2013) also focused on bank balance-sheet ratios and showed that liquidity played an important role in explaining credit risk and more specifically the CDS spread. Moreover, Chen et al. (2007), Fabozzi et al. (2007) and Annaert et al. (2013) find that liquidity is an important determinant of CDS spread. Our results also suggest that asset quality impacts CDS spread significantly and, in line with expectations, positively. This suggests that bank CDS spreads reflect risk captured by the bank balance sheet, i.e., the risk associated with their asset quality. More specifically, the ratio of impaired loans/equity proves to have a significantly positive link with banks'

CDS spread. The higher the ratio (i.e. as the ratio of impaired loans/equity increases), the more problematic the loan, and hence the positive coefficient of this ratio reflects higher credit risk due to the deterioration of asset quality. Graph 3 also supports this argument, where there is a positive relationship between the fluctuations of the ln(CDS) spread and asset quality, which in turn implies that higher impaired loans/equity lead to higher credit risk. This finding is consistent with Chiaramonte and Casu (2013), who proxy asset quality with the *Loan Loss Reserve to Gross Loans ratio,* and find this variable as a significant driver of CDS spread, indicating that the probability of default increases especially for banks that have low quality loan portfolios.

The third finding relates to the relationship between bank-level leverage and CDS spread. In fact, banks were heavily borrowing from capital markets when credit conditions were booming, and lending to financial institutions was made easy with consumers blindly investing their savings in banks expecting to earn interest. In addition, financial engineering and securitization also greatly contributed to the increased leverage intakes that banks were subject to. This was reflected in the deterioration of banks' asset quality. With the beginning of financial crisis, the true leverage ratios came to light revealing that most banks were borrowing well above the authorized norms. In fact, Ericsson et al. (2009) show that leverage, among other factors, explain approximately 23% of CDS spread fluctuations. Table 3 below indicates that the higher the leverage level, the wider the CDS spread, reflecting greater credit risk. Thus, banks that borrowed more aggressively experienced much higher CDS spread levels. During the financial crisis, the highly leveraged banks lost access to external funding when capital markets froze. In addition, consumers lost confidence in the banking sector and were withdrawing their savings. The control variables namely regulatory capital and operations income ratio are discussed in the following section. While regulatory capital remains insignificant as a factor driving credit risk, the operating income however does make play a significant role in explaining the variability of credit risk across banks.

4.2. Sensitivity to the definition of CDS determinants

We assess the sensitivity of the benchmark model to the choice of bank characteristics. Therefore, in estimating the models reported in Table 3, we: (i) replace the ratio of *Impaired Loans / Equity* with the ratio of *Impaired Loans / Gross*

Loans, as a measure of asset quality; (ii) replace the ratio of *Liquid Assets / Deposits & Short-term Funding* with the ratio of *Liquid Assets / Total Deposits & Borrowings* as a measure of liquidity; (iii) replace *Tier 2 Capital Ratio* by the *Total Capital Ratio* as a measure of regulatory capital (iv) replace the ratio of *Long-term Debt to Common Equity* by the ratio of *Equity / Total Assets* as a measure of leverage; (v) replace the ratio of *EBITA (Earnings Before Interest Tax and Earnings)/ Average Assets* by *Return On Average Equity (ROAE),* as an indicator of bank-level operations Income ratio.

The results show that the main findings remain unchanged. Therefore, any deterioration in the asset quality ratio leads to an increase in credit risk, while a rise in the degree of liquidity of the assets held by banks reduces their default risk in a significant manner. In addition, the results also show that the level of bank operations income ratio is negatively related to the CDS spread and credit risk. As for the regulatory capital and leverage, the findings from table 6 do not suggest a significant impact on banks' CDS spread. Yet, the coefficient associated with leverage variable is positive and significant for the pre-crisis period. Higher capital requirements tend to be costly for a financial institution and are usually perceived as a burden. The riskier a bank's portfolio, the more capital it will be required to hold. By being forced to keep a certain percentage of capital as a cushion in case there is a negative credit event, a bank's investment may be reduced, which decreases its competitiveness in financial markets. The insignificant effect of regulatory capital suggests that on average the impact of this variable on credit risk is neutral.

Table 3
Parameters estimation: robustness checks

Independent variable	(1)	(2)	(3)	(4)	(5)
Dependent variable:	CDS spread (ln)				
House Price Index (ln)	0.213 (1.075)	1.215 (1.224)	0.782 (1.364)	0.555 (1.325)	0.339 (1.253)
Liquidity (Liquid Assets / Tot Dep & Bor)	-0.017 (0.011)	-0.017 (0.011)	-0.021* (0.013)	-0.025** (0.012)	-0.023* (0.012)
Asset Quality		0.125***	0.119***	0.102***	0.044

	(1)	(2)	(3)	(4)	(5)
(Impaired Loans / Gross Loans)		(0.026)	(0.032)	(0.033)	(0.040)
Regulatory Capital (Total Capital Ratio)			-0.002 (0.033)	0.024 (0.035)	0.033 (0.037)
Leverage (Equity / Liabilities)				-0.089* (0.050)	-0.015 (0.048)
Operations Income Ratio (Return On Avg Equity)					-0.014*** (0.004)
Time dummies (joint)	70.75	31.83	19.14	17.16	17.43
Adjusted R^2	0.620	0.627	0.621	0.623	0.642
Hausman Specification test	27.44	7.91	14.23	10.45	6.94

Notes: The sample includes 115 banks in 20 countries from 2004 to 2011. All the models include time dummies. Heteroskedasticity and autocorrelation consistent standard errors are clustered by country and reported in brackets. *** (**), [*] stands for the variable being statistical significant at 1% (5%) [10%] s.l.

Besides, our results confirm the importance of bank operations income ratio, measured by (Return on Average Equity, ROAE), in lowering credit risk, as it has a negative and highly significant effect on bank CDS. The negative relationship between bank operating income and bank CDS spread is demonstrated in graph 5. In addition, one of the explanations of the insignificance of leverage as a driver of the CDS spread post-crisis relates to the fact that banks used off-balance sheet securitization in order to hide their real leverage intakes to finance their investment activities. In addition, this also translated into bank's ability to escape regulatory requirements by showing less leverage in their balance sheet. This is one of the reasons that explain the sensitivity of the leverage as a driver of the CDS spread in the pre-crisis period, but turned out insignificant in the post-crisis period in our final dynamic specification to be presented later in this section.

4.3. Is the impact of size on CDS spread non-monotonic?

Having decided the preferred model, we study the impact of bank's size upon the credit spread. Table 4 shows that bank size is positively correlated with CDS spread in terms of its direct effect. Bank size would grow as the bank total assets rise. The findings indicate that the bigger the bank, the higher the CDS spread. In fact, during the credit boom of early 2000, banks were enjoying high credit injections in the form of foreign funding inflows. This enabled them to expand their lending activities, mostly through the issuance of complex mortgage securities, which in turn boosted their profits. The idea of increasing their size in both domestic and international markets was appealing to these financial institutions. As such, the phenomenon of the *too-big* and the *too-important*-to-fail gave banks the wrong incentives to grow beyond their optimal size, believing that they would never collapse as the government would always be there to rescue them. However, as the recent financial crisis unfolded, many of these big financial institutions were left to go bankrupt. Therefore, bigger banks beyond a threshold level were subject to higher credit risk and wider CDS spreads. The financial institutions that were closely linked to the public, such as AIG, did benefit from a government bailout package.

To assess the empirical validity of the link between bank size and CDS spread, we introduce a quadratic term of bank size ($lnBank\ Size^2$). If the impact of size on CDS spread is non-monotonic, then at low levels of bank size, CDS spread moves negatively with bank size, while there is a critical threshold beyond which further increases in bank size lead to a rise in the CDS spread. However, in order to ensure that the U-shape relationship between the CDS spread and bank size really exists, it is essential to conduct the U-test by Lind and Mehlum (2010). More precisely, we have followed the approach adopted by Leonida et al. (2012), where the authors investigated the effect of political replacement effect in a panel of 102 countries over the period of 1980-2005 and tested for the presence of a U-shape relationship. In addition, they also tested for non-monotonicity in the relationship between political competition and economic reform, by examining whether the relationship is decreasing at low values and increasing at high values within the data range.

Table 4
Parameters estimation: the impact of size

Independent variable	(1)	(2)

Dependent variable:	CDS spread (ln)	
House Price Index (ln)	2.515 (1.729)	3.059* (1.735)
Liquidity (Liquid Assets / Dep & ST Funding)	-0.011 (0.007)	-0.010 (0.007)
Asset Quality (Impaired Loans / Equity)	0.026** (0.010)	0.027** (0.010)
Regulatory Capital (Tier 2 Capital)	-0.058 (0.116)	-0.062 (0.118)
Leverage (Long-term debt to equity)	0.023 (0.034)	0.017 (0.032)
Operations Income Ratio (EBITA / Avg Assets)	-0.341*** (0.105)	-0.401*** (0.109)
Size (ln Total Assets)	1.281** (0.619)	-7.036* (3.590)
$Size^2$ $(\ln \text{Total Assets})^2$		0.309** (0.132)
Time dummies (joint)	37.74	43.88
Adjusted R^2	0.790	0.796
Hausman Specification test	84.06	-5.160
Extreme Point		11.380
Slope at:		
Minimum (p-value)		-4.861 (0.041)
Maximum (p-value)		4.184 (0.003)
Test for U-shape (p-value)		1.820 (0.041)

Notes: The sample includes 115 banks in 20 countries from 2004 to 2011. All the models include time dummies. Heteroskedasticity and autocorrelation consistent standard errors are clustered by country and reported in brackets. *** (**), [*] stands for the variable being statistical significant at 1% (5%) [10%] s.l.

In our analysis, for each model, we report the interval, the slope estimated at the minimum and maximum values, the associated t -statistics, as well as the test for the overall significance of a U-shaped relationship. For all of the models, we also report the estimated extreme point together with the associated confidence interval estimated by the Fieller method. Our empirical analysis strongly supports the existence of a U shape relationship between bank CDS spread and bank size. The quadratic term of Bank Size is positive and statistically significant at 5% level, while the linear term is negative and also significant at 5% or 1% level across different models. In addition, the U-test proves that there is a U-shape relationship linking CDS spread and bank size. As such, these findings from table 6-8 are supportive of a non-linear relationship and allow us to derive from the estimated equation the critical value of bank size beyond which the CDS spread starts increasing. The U-test for all models in Tables 5-8 confirms the existence of the U-shape relationship. The threshold point can be derived from the estimated equation (5) with the static estimates.

This implies that the optimal bank size in terms of absolute values will be: *exp (10.46)* which approximately equals 35 billion Euros. From equation (5), it can be observed that the turning point is equal to 35 billion Euros. This point indicates that as bank size increases above this threshold, it causes the CDS spread to widen and the credit risk to subsequently go up. Thus, bank size and the CDS spread are negatively related up until the optimal size of the bank in terms of total assets. This implies that smaller banks face lower credit risk. After this threshold, bank size and the CDS spread become positively related, implying that the bigger the bank, the higher the CDS spread and credit risk.

The results show that the level of credit risk varies across big and small banks. As such, smaller banks typically experience narrower CDS spread and lower level of credit risk. They are therefore safer, although they do not have the same ability to diversify their risk portfolios as bigger financial institutions; these banks are considered to be more cautious with their investment decision-making process. This finding is in line with the literature on the *too-big-to-save*. Demirgüç-Kunt and Huizinga (2013) focused on equity prices and CDS spread in the context of public deficit and bailouts. Their findings show that the *too-big-to-save* hypothesis infers that large banks are typically subject to reduced bailout prospects particularly in countries that experience fiscal constraints. Therefore, bigger banks are considered to be riskier, while smaller banks, which conduct small size investment activities, are considered to be safer and more secure.

4.4. The role of time

Up to this point we have adopted very simple models to identify Banks CDS determinants. These empirical models do not take into account the time-varying changes in the determinants of Credit Default Swaps. The risk is that our models miss some important information in the CDS. The existing literature shows that CDS spreads are following a Markov Switching process. Alexander and Kaeck (2008), among others, show that there are regime dependent determinants for Credit Default Swaps. Accordingly, Kizys, Paltalidis and Vergos (2016) provide ample evidence for a Bayesian Markov Switching determinant for Banks and Sovereign Credit Default Swaps.

The implicit hypothesis our models did follow is that the impact of the explanatory variables on the dependent variable is constant over time. The approach is that because the data span is not long, this hypothesis is not a strong one. However, our sample period contains the 2007 crisis, and hence allows us to study the determinants of CDS spread under very different regimes. The next step of our analysis is to assume that two regimes exist, that in our case, are exogenously determined. We hence prefer to use this information to split the sample, instead of letting the data to determine it endogenously by using a regime switching model. This is justified by the 2007 financial crisis being the large event in the sample period. Hence, having determined a preferred model, we have estimated the same model in two sub-samples, i.e. before the crisis, and the remaining sample.

Results are reported in Table 5 which remain consistent for some variables as in the overall sample, namely operations income ratio and bank size along with showing non-monotonic effects. We however note that the model does not perform as good as when the sample is not split. This is likely due to the role on near collinearity. To check the extent to which this is the case, we have performed a general to specific approach, that leads to our preferred models, both for the entire period, and for the subsamples. Those results are reported in Table 6 and remain consistent with the overall sample with two exceptions namely leverage and bank size (in terms of the magnitude of its effect although the sign remains the same as in overall sample).

Table 5
Parameters estimation: the impact of time

Independent variable	(1)	(2)
Dependent variable:	CDS spread (ln)	
	time < 2007	time ≥ 2007
House Price Index (ln)	2.252 (1.461)	2.057 (2.421)
Liquidity (Liquid Assets / Dep & ST Funding)	-0.002 (0.002)	-0.019 (0.013)
Asset Quality (Impaired Loans / Equity)	-0.006 (0.003)	0.034** (0.015)
Regulatory Capital (Tier 2 Capital)	0.004 (0.082)	-0.050 (0.120)
Leverage (Long-term debt to equity)	0.074** (0.025)	-0.025 (0.041)
Operations Income Ratio (EBITA / Avg Assets)	-0.950*** (0.234)	-0.494*** (0.135)
Size (ln Total Assets)	-31.919*** (8.680)	-10.267* (5.157)
$Size^2$ $(\ln \text{Total Assets})^2$	1.135*** (0.309)	0.446** (0.190)
Time dummies (joint)	7.360	2.600
Adjusted R^2	0.908	0.639
Hausman Specification test	16.49	37.00
Extreme Point	14.056	11.513
Slope at:		

Minimum (p-value)	-23.932 (0.001)	-7.130 (0.037)
Maximum (p-value)	9.292 (0.002)	5.917 (0.002)
Test for U-shape (p-value)	3.550 (0.002)	1.860 (0.037)

Notes: The sample includes 115 banks in 20 countries from 2004 to 2011. All the models include time dummies. Heteroskedasticity and autocorrelation consistent standard errors are clustered by country and reported in brackets. *** (**), [*] stands for the variable being statistical significant at 1% (5%) [10%] s.l.

Leverage however has an opposite effect in both periods in the sense that while higher leverage added to higher credit risk in the pre-crisis period, it had a dampening effect in the post-crisis period which later turned insignificant in a dynamic model to be presented in the next sub-section.

Table 6. Parameters estimation: robustness to the General-to-Specific exercise

Independent variable	(1)	(2)	(3)
Dependent variable:	CDS spread (ln)		
	Entire period	time < 2007	time ≥ 2007
Liquidity (Liquid Assets / Dep & ST Funding)	-0.013** (0.006)		-0.017** (0.007)
Asset Quality (Impaired Loans / Equity)	0.015* (0.008)		0.012*** (0.002)
Leverage (Long-term debt to equity)	0.060** (0.027)	0.044** (0.016)	-0.278*** (0.069)
Operations Income Ratio (EBITA / Avg Assets)	-0.185** (0.087)	-0.829*** (0.092)	
Size (ln Total Assets)	-4.894** (1.909)	-24.342*** (5.695)	-4.339** (1.867)
$Size^2$ $(\ln \text{Total Assets})^2$	0.234*** (0.078)	0.880*** (0.195)	0.203** (0.080)

Time dummies (joint)	27.290	4.930	18.880
Adjusted R^2	0.714	0.988	0.493
Hausman Specification test	52.650	49.14	27.40
Extreme Point	10.458	13.824	10.663
Slope at:			
Minimum (*p*-value)	-3.248 (0.013)	-18.148 (0.001)	-2.907 (0.016)
Maximum (*p*-value)	3.598 (0.001)	7.614 (0.001)	3.046 (0.005)
Test for U-shape (*p*-value)	2.360 (0.013)	4.200 (0.001)	2.200 (0.016)

Notes: The sample includes 115 banks in 20 countries from 2004 to 2011. All the models include time dummies. Heteroskedasticity and autocorrelation consistent standard errors are clustered by country and reported in brackets. *** (**), [*] stands for the variable being statistical significant at 1% (5%) [10%] s.l.

4.5. Dynamics and endogeneity

We finally estimate a dynamic model. Results are reported in Table 7. The exercises show that the results are robust to a number of modification of the estimation method and the independent variables. According to the Arellano-Bond test, there is no evidence of second order autocorrelation; therefore, our model is correctly specified. The difference equation is instrumented with the one period lagged levels of the dependent variable, and the levels equation with the difference lagged one period. Moreover, we report Sargan-Hansen test that follows the Chi-squared distribution with (L-K) degrees of freedom, testing the validity of instruments. Under the null, the instruments included are uncorrelated with the error term, thus they are valid. The outcome of the Sargan test would indicate whether the equation is correctly identified or is over-identified. Under the null hypothesis, the equation is adequately and correctly identified. The alternative hypothesis states that the model is over-identified (i.e. the number of instruments is more than the number of endogenous variables). According to our findings from table 7, the *p-values* for the Sargan test for over-identifying restrictions, where the null hypothesis is that the instruments are uncorrelated with the residuals, confirm that the instruments are not correlated with the residuals and they are valid instruments. Furthermore, we are satisfying the condition whereby the number of instruments is 22 and is less than the number of groups, which is equal to 24. The lagged dependent variable is statistically significant reflecting a high degree of persistence in the variables during the pre-crisis period.

Table 7 reports the results from the GMM analysis which are consistent with the outcome obtained from both the benchmark model and the bank size model. Our findings indicate that the bank level determinants tend to drive credit risk. The positive relationship between asset quality and the CDS spread is demonstrated in table 7. As the ratio of impaired loans to equity increases, the quality of assets decreases. This implies that the bank becomes riskier when it holds a higher proportion of toxic assets. Before the recent financial crisis, banks heavily invested in highly structured products that were associated with very high risks. This was particularly easy with the increased popularity of securitization activities and financial engineering. As the crisis began, many of banks' assets started defaulting due to their toxic nature. This was despite the excessively high rating most structured products enjoyed before the beginning of the crisis. In fact, credit rating agencies played a predominant role in boosting the ratings of highly risky instruments to increase their marketability. The GMM results are in line with the previous findings and confirm the hypothesis, which stipulates that a bank with more reliable quality of assets will face reduced credit risk.

Furthermore, the findings also illustrate the negative relationship between the CDS spread and bank liquidity. As such, banks with higher levels of liquidity were in a better position to avoid bank-runs that resulted from the recent financial crisis. From summer 2007, both money markets and capital markets stopped lending to banks and other financial institutions. Therefore, financial markets froze. In addition, investors' sentiment reached its lowest level as consumers and lenders lost trust in the financial system and decided to withdraw their deposits from banks. The only financial institutions that were able to withstand the crisis were those that kept high liquidity levels and were able to sustain themselves despite the lemon markets. Thus, the banks that had high levels of liquidity were subject to tighter CDS spread and lower credit risk.

Moreover, table 7 shows evidence of a negative relationship between the level of bank operating income ratio *(EBITA / Average Assets)* and the CDS spread. As such, banks that are more profitable are better able to cope with negative credit event and are considered to be stronger as compared to banks that have low levels of operating income ratio, in line with the initial hypothesis.

Last but not the least, the results in table 7 demonstrate that, on average, the CDS spread and bank size are positively related. Once the quadratic term is included to capture non-linearity, there is clear evidence in favour of a non-linear relationship that the smaller banks faced narrower CDS spread levels and credit risk as they were deemed to be safer relative to bigger banks. For bigger banks with assets beyond a critical level, we find that the CDS spread is positively related to bank size. In order to reassert our previous findings, after having conducted the GMM analysis, we follow Leonida et al. (2012) and Lind and Mehlum (2010) to undertake the U-test which strongly supports the evidence that there is a U-shape relationship linking bank CDS spread and bank size. The outcome from U-test conducted following the GMM estimation allows us to conclude that bank size and the CDS spread are negatively related up until bank size reaches a certain threshold. After that threshold, the relationship between bank size and credit risk turns into becoming positive, meaning that the bigger the bank, the wider the CDS spread and vice versa. As such, when bank size goes up, the CDS spread level moves inversely with bank size. There is a critical threshold beyond which further rise in bank size leads to an increase in the CDS spread.

Table 7
Parameters estimation: Dynamic model

Independent variable	(1)	(2)	(3)
Dependent variable:	CDS spread (ln)		
	Entire period	time < 2007	time ≥ 2007
CDS spread (ln)$_{t-1}$	0.182*** (0.054)	0.703*** (0.160)	0.199*** (0.076)
Liquidity (Liquid Assets / Dep & ST Funding)	-0.020*** (0.006)	-0.004*** (0.001)	-0.039*** (0.010)
Asset Quality (Impaired Loans / Equity)	0.015*** (0.003)	0.006** (0.003)	0.022*** (0.005)

Leverage (Long-term debt to equity)	-0.014 (0.014)	0.350*** (0.070)	-0.024 (0.037)
Operations Income Ratio (EBITA / Avg Assets)	-0.311*** (0.059)	-0.781*** (0.119)	-0.427*** (0.100)
Size (ln Total Assets)	-2.409* (1.424)	-15.628** (7.515)	-4.730** (1.903)
Size^2 (ln Total Assets)^2	0.108** (0.054)	0.546** (0.273)	0.212*** (0.075)
Time dummies (joint)	78.420	4.580	4.320
Extreme Point	11.144	14.305	11.135
Slope at:			
Minimum (p-value)	-1.648 (0.058)	-11.785 (0.022)	-3.235 (0.011)
Maximum (p-value)	1.514 (0.003)	4.198 (0.049)	2.979 (0.001)
Test for U-shape (p-value)	1.580 (0.058)	1.710 (0.049)	2.350 (0.011)

Notes: The sample includes 115 banks in 20 countries from 2004 to 2011. All the models include time dummies. Heteroskedasticity and autocorrelation consistent standard errors are clustered by country and reported in brackets. *** (**), [*] stands for the variable being statistical significant at 1% (5%) [10%] s.l.

Following the estimated GMM results in Table 7, we can derive the bank size optimal point as follows: the optimal bank size in terms of absolute values will be *exp*(11.153) which approximately equals 70 billion Euros. Therefore, as long as bank total assets are below or equal to 70 billion Euros, bank size and the CDS spread will exhibit a negative relationship. Even with the dynamic GMM approach, there is still a critical level of bank size, although the threshold point is at a higher level compared to the optimal size derived in the fixed effects estimation. After this point, bank size and the CDS spread become positively related. Thus, bigger banks face more risk, while smaller banks are safer given that they experience narrower CDS spreads.

Considering the estimates in the two sub-periods, we however find a different extreme point of bank size (see Table 7) for the pre-crisis period which clearly reflects an increasing risk only for extremely big banks. The optimal bank size for the pre-crisis period in terms of absolute values was *exp*(14.305) which approximately equals 1642 billion Euros. The turning point has become significantly lower in the post-crisis period at around 70 billion. It is probably for this reason Barth and Schnabel (2013) argued that bank size is not a satisfactory measure of systemic risk because it neglects aspects such as interconnectedness, correlation, and the economic context. To address extreme shocks of this magnitude or to disentangle the effect of systemic risk which rose sharply at the onset of the financial crisis in August 2007, we estimated the model in two sub-periods to determine the optimal bank size during the two regimes. In the pre-crisis regime when extremely big size banks experienced an increase in CDS spreads, implying too-big-to-fail or too-systemic-to-fail and too-big-to-save using government bailout funds. We conclude that the identification of the optimal bank size can be contingent on the level of economic or financial condition (whether inflationary (pre-crisis) or deflationary (post-crisis) regimes).

5. Conclusion

This paper explores the key bank level drivers of bank CDS spreads during 2004-2011, across 30 countries covering 115 banks. Most importantly, this research significantly contributes to the existing literature as it looks at the impact of bank size on the CDS spread and uncovers several important findings relating to optimal size of banks and credit risk.

We find that the fluctuations of bank CDS spread strongly depend on: (i) the quality of the bank's balance sheet; (ii) liquidity of banks' assets; and (iii) how profitable banks' operations are. As such, banks' with better asset quality are subject to less credit risk. In addition, higher liquidity enables banks to avoid bank-runs and be more resilient to bankruptcy and insolvency. Finally, banks with higher levels of operating income ratio have more income to withstand a negative credit event such as the recent financial crisis, and therefore face lower CDS spread. We find that both regulatory capital and leverage appear to have a reduced ability to explain the variations in credit risk over the sample period. The results are consistent across different methods of estimation including both static and dynamic models (FE, RE and the GMM estimations).

When considering the impact of bank size on the CDS spread, we demonstrate that total assets and credit risk are negatively related up until a certain point, which we refer to in this paper as "bank optimal size". Before this point, banks are considered to be either small or average, and are typically subject to reduced risk. After that point, bank size and the CDS spread become positively related, meaning that the bigger the bank, the higher the CDS spread. Our findings are in line with the previous literature on the *too-big-to-save*. In fact, while most banks during the credit expansion were trying to grow beyond their optimal size thinking that they will benefit from government support in case of a negative credit event, the recent financial crisis revealed that not all big banks are systematically saved. This leads us to the conclusion that smaller and medium sized banks are safer than large banks. Considering the estimates in the two sub-periods, we found a different extreme point of bank size in the pre-crisis period (approximately 1642 billion Euros) relative to a significantly lower level of optimal bank size (around 70 billion) in the post-crisis period, implying the case of too-big-to-fail and too-big-to-save in the pre-crisis regime, and a lower threshold level of bank size in the post-crisis period indicating reduced level of systemic risk in the banking sector globally.

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Table A.1
List of Banks

ABN Amro Bank	CREDIT LYONNAIS	Lloyds Banking Group PLC
ABU DHABI COMR BK	CREDIT SUISSE GROUP	MIZUHO CORP BANK LTD
AKBANK TURK ANONIM	Caixa Geral De Depositos	MORGAN STANLEY
ALFA-BANK (OJSC)	Capital One Financial Corp	Malayan Banking Berhad
ALPHA BANK A.E.	China Development Bank	Mediobanca
AOZORA BANK, LTD	Commerzbank	NAT BK OF ABU DHABI
Alliance and Leicester Commercial Bank	Credit Agricole	NAT BK OF GREECE SA
BAWAG P.S.K	DANSKE BANK A/S	NATIONAL AUS BK
BAYERISCHE LANDESBK	DBS BANK LTD	NORD-LB – GIRO
BCP FINANCE BK	DEV BK OF JAPAN INC	NORDEA BANK AB
BNP Paribas	DNB NOR BANK ASA	Nationwide Building Society
Banca Intesa	DZ Bank	Natixis
Banca Italese	Deutsche Bank	Northern Rock PLC
Banca Monte Dei Paschi	Dexia	OS CHINESE BKG CORP LTD
Banca Nazionale del Lavoro	EFG Eurobank Ergas	RAIF ZNTRLBK OSTER AG
Banca Popolare Di Milano	EMIRATES NBD (PJSC)	RHB Bank Berhad
Banco BPI	ERSTE GROUP BANK AG	Rabobank Nederland
Banco Bilbao Vizcaya Argentaria SA	Export-Import Bank of China	Rosselkhosbank
Banco Comr Portugues	Fortis Bank	SHINHAN BANK
Banco Espirito Santo SA	GAZPROMBANK (OJSC)	SKANDINAVISKA ENSK BNKN
Banco Pastor SA	HANA BANK	SNS Bank
Banco Popolare Italiana	HBOS	Sberbank of Russia
Banco Popular	HSBC Holdings PLC	Societe Generale
Banco Santander SA	ICICI Bank limited	State Bank of India
Banco de Sabadell SA	IDBI Bank LTD	THE BTMBI UFJ LTD
Bank of America Corporation	IKB Deutsche Industrial Bank	THE CO-OP BANK PLC
Bank of China Limited	IND & COM BK OF	THE EXPT-IMPT BK OF

	CHIN	KOA
Bank of India	INDL BK OF KOREA	THE GOLDMAN SACHS GP
Bank of Moscow	ING Bank	THE KOREA DEV BANK
Bankinter	Irish Life and Permanent Plc	THE RBS GROUP PLC
Barclays	JP Morgan Chase & Co.	TURKIYE IS BANKASI
CAIXA D'ESTL DE CATA	JSC BK CENTERCREDIT	UBS AG
CAIXA PNOS DE BARCA	KBC Group	Unicredito Italiano
CATHAY UNITED BK CO LTD	KOOKMIN BANK	Unione Di Banche Italia (UBI Banka)
CDA DE VLNCIA CASTLN	KOREA EXCHANGE BANK	VTB Bank
CDA DEL MEDITERRANEO	LANDESBANK BERLIN AG	WESTLB AG
CDA Y MP DE MADRID	LB BADENWUERTTEMBERG	WESTPAC BANKING CORP
CIMB BANK BERHAD	LB HESSTHRGN GIRO	WOORI BANK
CITIGROUP INC.		

Table A.2
List of Countries

Australia
Austria
Belgium
Cayman Islands
China
Denmark
France
Germany
Greece
Hong Kong
India
Ireland
Italy
Japan
Kazakhstan
Malaysia
Netherlands
Norway
Portugal
Russia
Singapore
South Korea
Spain
Sweden
Switzerland
Taiwan
Turkey
UAE
UK
US

Appendix: The Principal Component Analysis

To examine the potential impact of the existence of commom components in the set of regressors, we have conducted the Principal component analysis, whose results are summarized in this appendix. Being mainly interested in the likely non-monotonic impact of bank size on CDS spread, we have examined the role of the principal common components in determining the CDS spread by keeping bank's size outside the analysis. Results are reported in the Table A.3.

Table A.3.
The Principal Component Analysis

Independent variable	(1)	(2)
House Price Index (ln)	3.059* (1.735)	2.065 (1.643)
Liquidity (Liquid Assets / Dep & ST Funding)	-0.010 (0.007)	
Asset Quality (Impaired Loans / Equity)	0.027** (0.010)	
Regulatory Capital (Tier 2 Capital)	-0.062 (0.118)	
Leverage (Long-term debt to equity)	0.017 (0.032)	
Operations Income Ratio (EBITA / Avg Assets)	-0.401*** (0.109)	
1st Common Component		0.066** (0.025)
2nd Common Component		0.028** (0.014)
Size (ln Total Assets)	-7.036* (3.590)	0.879 (7.676)
$Size^2$ $(\ln \text{Total Assets})^2$	0.309** (0.132)	0.036 (0.276)
Time dummies (joint)	43.88	21.15
Adjusted R^2	0.796	0.744
F-statistics for the joint exclusion of:		
All regressors but time dummies	15.41	14.61
All regressors but time dummies and Size and $Size^2$	10.54	6.44

All regressors but time dummies and Size	9.14	5.70

Notes: The sample includes 115 banks in 20 countries from 2004 to 2011. All the models include time dummies. Heteroskedasticity and autocorrelation consistent standard errors are clustered by country and reported in brackets. *** (**), [*] stands for the variable being statistical significant at 1% (5%) [10%] s.l.

Results suggests that there are two common components, and they can explain about 70% of the total variance. When added to the set of regressors in the place of the set of variables generating these, the model has a lower adjusted R^2, with respect to the standard model. Moreover, the variable size and its squared values are not statistically significant. The two common components are statistically significant. However, the analysis of the F-statistic shows that this is because of multicollinearity between the common components and the size variable. In the light of these considerations, we have preferred the traditional model which we have reported in the main text.

Research Highlights

1. *In the wake of the recent global financial crisis, this paper re-examines the role of bank size on their credit default swap (CDS) spreads during pre- and post-crisis periods.*
2. *CDS spread is driven by asset quality, liquidity and operations income ratio, with bank size showing a non-monotonic impact.*
3. *An optimal level of bank size exits, and banks growing beyond this threshold are subject to higher credit risk, implying that smaller and medium sized banks are safer than large banks.*
4. *In the pre-crisis regime, a different extreme point of bank size is found at 1642 billion Euros, relative to a significantly lower level of optimal size at 70 billion Euros in the post-crisis period.*
5. *A higher optimal level does reveal evidence for too-big-to-fail and too-big-to-save in the pre-crisis regime, showing the case of systemic instability.*